FORECASTING MACRO TARGETS OF THE TURKISH ECONOMY FOR THE YEAR 2000: AN APPLICATION OF BOX-JENKINS AND EXPONENTIAL SMOOTHING METHODS

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ABSTRACT

The basic macroeconomic targets of the Turkish economy for the year 2000 and thereafter are to reduce the interest rates to plausible levels and increase the total production in a steady way. The goal of this study is to see if the Turkish government can realize these targets for the year 2000. For this purpose, I employed, here in this study, two widely used forecasting techniques; Box-Jenkins and exponential smoothing procedures to forecast monthly future values of interest rates on deposits and industrial production index. Forecast outputs indicate that interest rate tends to decrease and industrial production index tends to increase. Therefore, it can be concluded that these forecasting methodologies verify that government's main macro targets will be most likely realized for the year 2000.

Keywords: Turkish Economy, Forecasting, Macro Targets, Box-Jenkins Method, Exponential Smothing Method,ARIMA Procedure.

1. Introduction

Turkey has been in a transition from government control of large segments of her economy to a market economy to closer tights to the world economy for last two decades. This slow transition and deviations from long-run goals led to usually undesirable macroeconomic indicators such as high interest rates and unstable growth rates till the end of 1999.

Since the beginning of 2000, Turkish economy has been experiencing a positive trend and optimistic expectations. Turkey's acceptance as a candidate member by EU, taking steps towards having a consensus by both public and private sectors to meet the basic requirements of EU membership, credible announcements by government and central bank to implement the proper monetary and fiscal policies formed a basis for optimistic expectations for the Turkish economy in general. Increasing the total production in a steady way and reduction the real interest rates to plausible levels are the government's main macroeconomic targets for the year 2000 and the following years.

In this study, forecasting analyses are carried out to see what will happen to the interest rates and production index by using two different time series methods i.e. Box-Jenkins and exponential smoothing methods. In Box-Jenkins methodology, first, identification, estimation and diagnostic checking procedures are applied to time series, then, future monthly observations of the

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series are forecasted. Same series are forecasted by choosing the best exponential smoothing option among others.

2. Box-Jenkins Or ARIMA Procedure

ARIMA stands for autoregressive (AR) integrated (I) moving average (MA). The general model for ARIMA can be written as

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + ... + \theta_q e_{t-q} . \quad (1)$$

This model is known as ARIMA (*p, d, q*). *p* is the number of lagged values of *y*, *d* is the number of times *y* is differenced to make it stationary, and *q* is the number of the lagged values of the error term. If the series is already stationary, then the model becomes ARIMA (*p, 0,q*) or ARMA (*p, q*). This model is used to explain/forecast the series that is assumed to depends on its past behavior (Kennedy, 1996, p.248). Before forecasting a series by Box-Jenkins (BJ) (or ARMA) methodology, we need to follow the steps below.

a) Stationarity Test: We look at the graph of the series. If series tends to drift somewhat with no obvious mean, we suspect that the series is nonstationary. A time series with constant mean and constant variance over time is called stationary. Besides, we examine the sample autocorrelation function (SAF) of the series. A SAF that dies down very slowly is another implication of nonstationarity (Montgomery, *et al*., 1990, pp.255, 271).

After all, we can run Dicky-Fuller (DF), Augmented DF or Phillips-Perron tests to see if the series is stationary. If the series is found nonstationary, its first difference is taken. In case the series is still found nonstationary, a higher order (i.e. second or third) difference is taken until series becomes stationary.

b) Identification: Behavior of theoretical SAF and sample partial autocorrelation function (SPAF) for stationary models is given the table below.

Model	**SAF**	**SPAF**
AR(*p*)	Tails off	Cuts off after lag *p*
MA(*q*)	Cuts off after lag *q*	Tails off
ARMA(*p, q*)	Tails off	Tails off

The expression tails off implies that function decays in an exponential, sinusoidal, or geometric fashion, approximately, with nonzero values. Cuts off indicate that function truncates abruptly with only a very few nonzero values (Montgomery, *et al*., 1990, p.261).

To determine the *p and q* values of an ARMA (*p, q*), we obtain the SAF and SPAF of the series and examine the SAF coefficients (r_k) and SPAF coefficients (r_{kk}). The numbers of lags in SAF and SPAF are taken one-third or one-fourth of the sample size in practice.

The coefficients r_k and r_{kk} that lie outside the 95% confidence interval will determine the AR (*p*) and MA (*q*). The 95% confidence interval is obtained from the formula of ($\mp 1.96\,(1/\sqrt{n})$. For instance, let us assume the number of observations in a series be 100. Standard error and confidence interval in this case would be 0.1 and $-0.196 \leq r_k, r_{kk} \geq 0.196$ respectively. Let us assume that first coefficient of SAF, r_1, is 0.435, second coefficient of SAF, r_2, is 0.340, first coefficient of SPAF, r_{11} is 0.435 and that all other coefficients are lower than 0.196 in absolute values. Then tentative model would be ARMA (1,2) for this series that is assumed to be stationary. In other words, coefficients of SAF (1), SPAF (1) and SPAF (2) are statistically different from zero at the 95% confidence interval. In the identification stage, we should take into account for the seasonality of the series as well. If there is seasonality and nonstationarity in the data, it is necessary to take the first difference of the already seasonally differenced data (Enders, 1995, pp.115, 117).

c) Estimation: In the example above, we use the regression of the series on AR (1), MA (1) and MA (2). Namely, $y_t = m + \phi_1 y_{t-1} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2}$. If the sample mean of the series is small enough in comparison with the observations in the series, we may not include constant term in regression (Montgomery, *et al.*1990, p. 270s). If there were seasonality at quarterly data, model above would be

$y_t = m + \phi_1 y_{t-1} + \phi_4 y_{t-4} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2}$, or

$y_t = m + \phi_1 y_{t-1} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_4 e_{t-4}$ (Enders, 1995, pp.109-117). (2)

d)Diagnostic Checking:

i) Regression residuals should be white noise. In other words, Ljung-Box-Q statistic value of the residuals should be less than chi-square tabled value at desired significance level.

ii) Coefficients of AR (*p*) and MA (*q*) obtained from the regression should be statistically different from zero.

iii) Model should be parsimonious that is, in its simplest form. This condition implies that a simple model should be preferred to a higher level model. Provided that ARMA (1,2) and, for instance, ARMA (1,6) meet all the previous conditions mentioned above, ARMA (1,6) model might be eliminated (Enders, 1995, p.96; Gaynor and Kirkpatrick, 1994, pp., 426, 431).

iv) Model should have a small root mean square error (standard error).

3. Exponential Smoothing Procedure

Exponential Smoothing forecast for any period is a weighted average of all the past values with weights declining geometrically. The basic exponential smoothing model (ES) can be written as

$$\bar{y}_t = \alpha y_t + (1-\alpha)\bar{y}_{t-1}, \tag{3}$$

where $\bar{y}_t$ is smoothed average for time t, y_t is actual value of the time series in period t, $\bar{y}_{t-1}$ is smoothed average for the previous time period and α is smoothing constant, ($0 \leq \alpha \leq 1$). Therefore,

$$\bar{y}_{t-1} = \alpha y_{t-1} + (1-\alpha)\bar{y}_{t-2} \tag{4}$$

$$\bar{y}_{t-2} = \alpha y_{t-2} + (1-\alpha)\bar{y}_{t-3} \tag{5}$$

$$\bar{y}_{t-3} = \alpha y_{t-3} + (1-\alpha)\bar{y}_{t-4} \tag{6}$$

Finally, substituting equation (4), (5) and (6) in equation (3), we obtain,

$$\bar{y}_t = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \alpha(1-\alpha)^3 y_{t-3} + \alpha(1-\alpha)^4 \bar{y}_{t-4} \tag{7}$$

We can also make appropriate substitutions for $\bar{y}_{t-4}, \bar{y}_{t-5}$ and so on until $\bar{y}_t$ can be expressed by its past weighted values. Suppose that sample size is 10 representing the actual values for period 1, 2,.., 10 and that we are interested in using ES to aid in analyzing these data. First equation to be smoothed would be $\bar{y}_2 = \alpha y_2 + (1-\alpha)\bar{y}_1$. Since $\bar{y}_1$ is not available at hand, we take $\bar{y}_1 = y_1$ as initial value. As indicated in equation (7), the weights decrease exponentially (or geometrically), equation (7) is called exponentially distributed or ES (Daniel and Terrell, 1995, p. 783).

Forecasting model by simple ES is

$$F_{t+1} = \alpha y_t + (1-\alpha)F_t, \tag{8}$$

where F_{t+1} is the forecast for period t+1, F_t is the forecast for period t. When we use simple ES, F_{t+1} and F_t would equal $\bar{y}_t$, $\bar{y}_{t-1}$ respectively. To start the calculations, we let F_t equal the actual value in period t, y_t and hence $F_t = y_t$ (Anderson, et al., 1996, p.709). Another way of obtaining initial forecast, F_t, is to take the mean of several past actual values of y_t (Daniel and Terrell, 1995, p.819, Montgomery, *et al*., 1990, p.87). In the same manner,

$$F_{t+2} = \alpha y_{t+1} + (1-\alpha)F_{t+1} = \alpha y_{t+1} + (1-\alpha)y_t \qquad (9)$$

$$F_{t+3} = \alpha y_{t+2} + (1-\alpha)F_{t+2} = \alpha y_{t+2} + \alpha(1-\alpha)y_{t+1} + (1-\alpha)^2 y_t \qquad (10)$$

Hence, as is shown in equation (10), F_{t+3} is a weighted average of the first three actual values of the series. The sum of the coefficients, or weights, for y_{t+2}, y_{t+1} and y_t equals one. In general, forecast for any period is a weighted average of all the past values.

We can extend the basic/simple ES equation to an equation that includes trend and/or seasonal components. A multiplicative seasonal model can be written as,

$$y_t = (a + b_t)S_t + e_t, \qquad (11)$$

where, y_t is actual value for period 1, a is permanent component (or deseasonalized average), b is unit trend component (slope or linear trend component), S_t is multiplicative seasonal factor and e_t is random error component. In multiplicative model, magnitudes of seasonal factor grow along with the series. Forecasting equation for the next period is

$$F_{t+1} = (a_t + b_t)S_{t-L+1}, \qquad (12)$$

and a forecast for k periods into the future can be written as

$$F_{t+k} = (a_t + b_t k)S_{t-L+k}, \qquad (13)$$

where L is the number of time periods in a seasonal cycle. For instance, for a monthly data, L is 12 (Daniel and Terrell, 1995, pp.823-824, Montgomery, et al., 1990, pp.137-145). Equation (11) is frequently called Holt-Winters method. Additive form of equation (11) is

$$y_t = a + b_t + S_t + e_t,$$

where S_t is additive seasonal factor (Montgomery, *et al*., 1990, pp.145-150). In this model, magnitudes of seasonal factor do not grow along with the series.

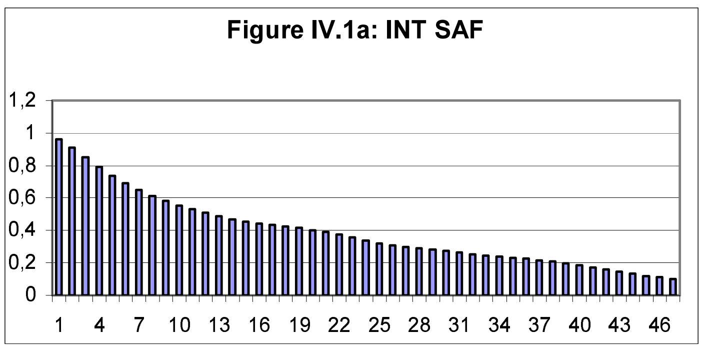
4. Stationarity, Identification, Estimation and Diognasting Checking Analyses for ARIMA Models

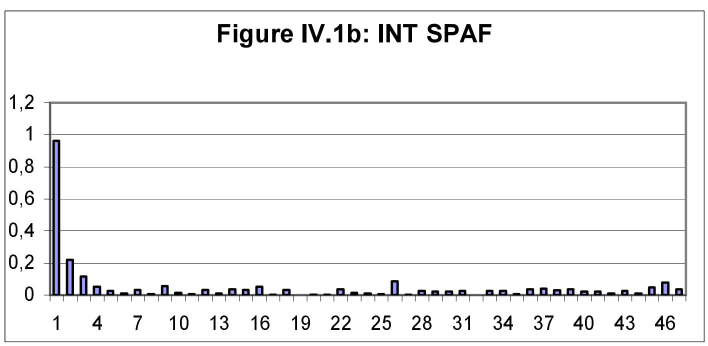
I used the monthly data on interest rates on deposits-twelve month (85:1-00:7) and industrial production index (85:1-00:6). The source for these series is Central Bank of Turkey Electronic Data Delivery System (EDDS). The definitions for interest rates and production index in the source are

TP.FA.FO7:12 Month and *TP.UR4.TO1: Total, 1997=100* respectively. In this section, several analyses are run to see if the series are stationary or not. Correlograms and DF/ADF tests of the series will help us to see whether INT and IP variables have constant mean and variance over time. Then we can continue on forecasting analyses of these stationary series. I used EViews 2.0 and RATS 4.2 programs throughout this study.

4. INTEREST RATES (INT)

Table 4.1: DF/ADF test results for INT		DF/ADF tests	%5 critical value	Q stat. for residuals	p of Q
a	$\Delta X_t = \alpha X_{t-1} + u_t$	-0.582	-1.94	54.45	0.21
b	$\Delta X_t = a + \alpha X_{t-1} + u_t$	-0.989	-2.87	54.21	0.21
c	$\Delta X_t = a + bt + \alpha X_{t-1} + u_t$	0.113	-3.43	56.28	0.16



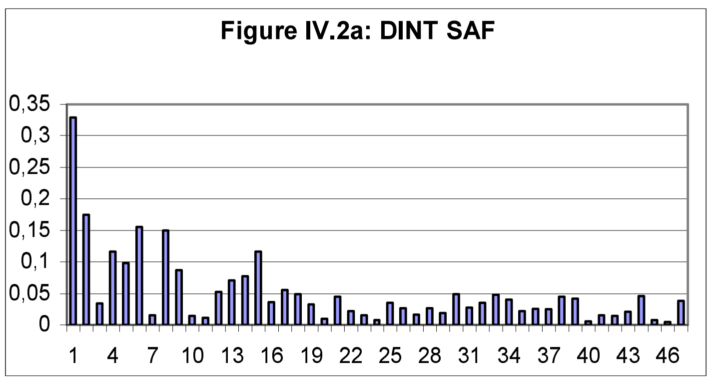


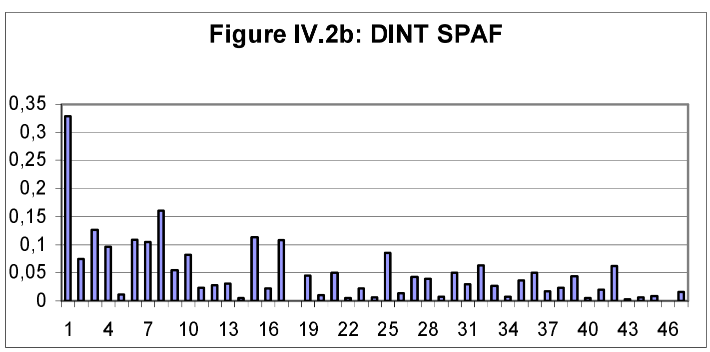
Having examined unit root tests and correlograms, INT series were found nonstationary. %5 critical values exceed the computed DF test values in absolute terms and SAF for INT is dying down slowly as seen in Figure IV.1a. Q statistic of SAF at lag 47 is 2433.9. Chi-square value at %5 significance level for lag 50 is 67.50. Therefore, both DF results given in Table 4.1 and Figures IV.1a and IV.1b conclude that INT series is not stationary.

Therefore, in order for us to be able to proceed the ARMA analysis, we need to take differences of INT series until it becomes stationary. Section IV.2 will go on analyzing for differenced INT.

4.2 DIFFERENCED INT (DINT)

Table 4.2a: DF/ADF test results for DINT		DF/ADF tests	%5 critical value	Q stat. for residuals	p of Q
a	$\Delta X_t = \alpha X_{t-1} + u_t$	-9.621	-1.94	24.52	0.99
b	$\Delta X_t = a + \alpha X_{t-1} + u_t$	-9.600	-2.87	24.52	0.99
c	$\Delta X_t = a + bt + \alpha X_{t-1} + u_t$	-9.694	-3.43	25.86	0.99





All DF test results show that DINT is stationary at %5 level. Q statistics indicate that we do not need to add ΔX_{t-i} to any of DF equations above in Table 4.2a. Figure IV.2a gives SAF that is not dying slowly and Q statistic value of DINT for lag 47 is 54.517, whereas chi-square value for 50 df at 0.05 is 67.504. These indicators also a verification for stationarity of the DINT time series. Next step is the identification of differenced INT by the help of correlograms. SAF and SPAF give us initial or tentative model in which the AR and MA terms correspond the r_{kk} and r_k that exceed the confidence interval of 0.143. Hence the model here at second column is the tentative model.

Table 4.2b: Estimates of DINT

	AR(1,8) MA(1,2,6,8)	AR(8) MA(1,2,6,8)	AR(0) MA(1,2,6,8)	AR(0) MA(1,2,6)
m	-0.121(-0.292)	-0.126(-0.297)	-0.130(-0.295)	-0.108(-0.288)
ϕ_1	0.174(1.851)	---------	---------	---------
ϕ_8	-0.240(-2.474)	-0.144(-1.141)	---------	---------
θ_1	0.133(3.021)	0.244(4.483)	0.264(4.314)	0.254(3.757)
θ_2	0.240(4.157)	0.293(4.565)	0.308(4.711)	0.315(4.626)
θ_6	-0.291(-641.61)	-0.230(-3.641)	-0.236(-3.642)	-0.253(-3.613)
θ_8	0.500(8.315)	0.396(3.956)	0.276(3.946)	---------
s.e.R	3.801	3.825	3.750	3.865
SSR	2471	2517	2546	2719
AIC	2.709	2.716	2.670	2.725
SBC	2.834	2.825	2.757	2.794
Q(n/4)	11.172(1.00) (lags = 44)	11.603(1.000) (lags = 44)	12.344(1.000) (lags = 47)	22.739(0.997) (lags = 47)

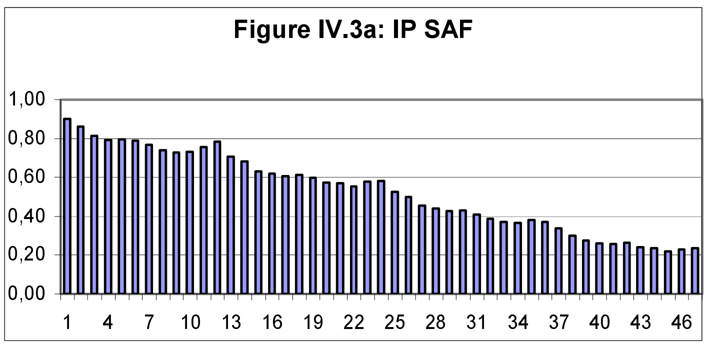
The values of estimated parameters, t statistics (in parentheses), standard error of regression (s.e.R.), sum of squared residuals (SSR), Akaike information criterion (AIC), Schwartz-Bayesian criterion (SBC), Q statistic for the autocorrelation of the n residuals and significance levels of Q statistic (in parentheses) are given in Table 4.2b.

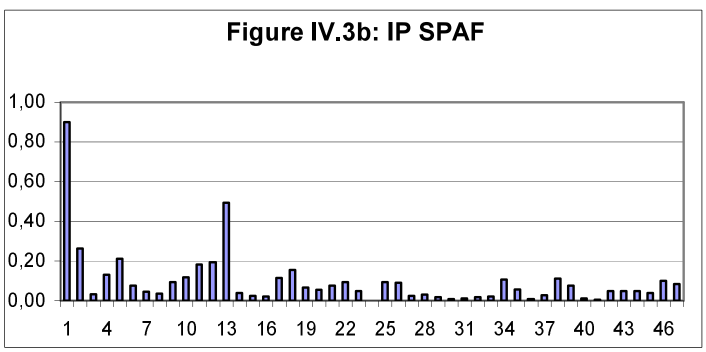
At second column, except constant and AR (1), all are statistically significant at 0.01 level. At third column, except constant and AR (8), all are statistically significant at 0.01 level. At column four, except constant, all are statistically significant at 0.01 level and at fifth column, except constant, all are statistically significant at 0.01 level. When we excluded the constant term from the equations, results did not change.

In terms of goodness-of-fit measures, except SSR, ARIMA (0,1,8) model seems the best among others. The p values of t statistics for MA (1), MA (2), MA (6) and MA (8) are less than 0.01 level. Residuals from this model are white noise. Insertion of MA (12) into the final model gave an insignificant parameter. Then the final model to be forecast would be the one at column four with the parameters of constant, MA (1), MA (2), MA (6) and MA (8).

4.3 INDUSTRIAL PRODUCTION INDEX (IP)

Table IV.3: DF/ADF test results for IP		DF/ ADF tests	%5 critical value	Q stat. for residuals	p of Q
a	$\Delta X_t = \alpha X_{t-1} + u_t$	1.786	-1.94	34.46	0.78
b	$\Delta X_t = a + \alpha X_{t-1} + u_t$	-1.274	-2.87	52.89	0.12
c	$\Delta X_t = a + bt + \alpha X_{t-1} + u_t$	-3.152	-3.43	52.31	0.13





ADF test results in absolute terms are less than the %5 critical values. Therefore, equation a, b and c give the result of nonstationary IP. Q statistics for residuals from these equations suggested that ADF equations in which lag(s) of differenced IP are employed are necessary, since these residuals initially were found autocorrelated (not white noise). In other words, to be able to get white noise residuals, we added several lags of differenced IP in each equation shown in Table 4.3a. For equation a, b and c, the lag numbers included are 18, 15 and 15 respectively. Figure IV.3a and IV.3b give the impression to us that industrial production index time series is not stationary, since SAF for IP is dying down slowly. Next section analyze the differenced IP (DIP).

4.4 DIFFERENCED IP (DIP)

Table IV.4a: DF/ADF test results for DIP		DF/ADF tests	%5 critical value	Q stat. for residuals	p of Q
a	$\Delta X_t = \alpha X_{t-1} + u_t$	-2.484	-1.94	41.41	0.49
b	$\Delta X_t = a + \alpha X_{t-1} + u_t$	-3.877	-2.87	52.86	0.12
c	$\Delta X_t = a + bt + \alpha X_{t-1} + u_t$	-3.944	-3.43	53.31	0.11

Figure IV.4a: DIP SAF

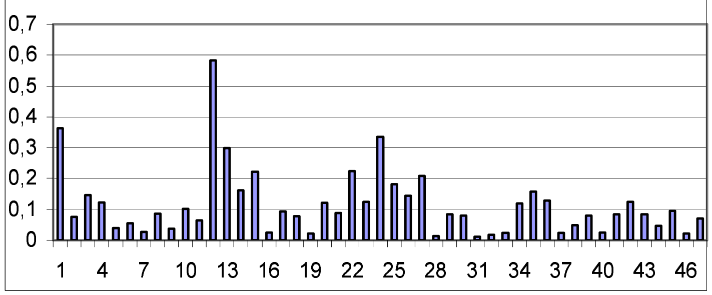


Figure IV.4b: DIP SPAF

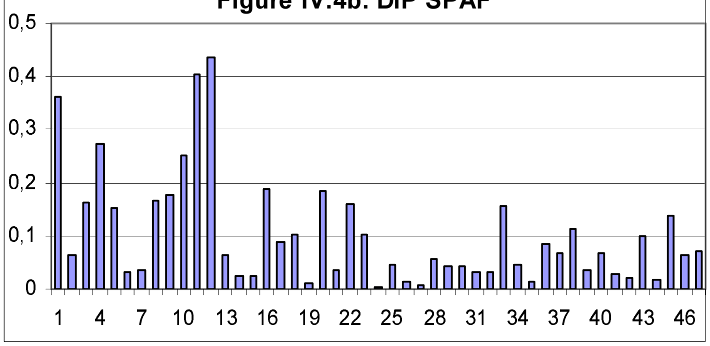


Table 4.4a results in a stationary time series of DIP. Several lags of differenced DIP were added in each equation shown in Table 4.4a to get the white noise residuals. For equation a, b and c, the lag numbers included are 15,

14 and 14 respectively. Figure IV.4a also confirms the stationarity result with a function dying down almost rapidly.

At second column in Table IV.4b, the only parameters of AR (4), AR (10), AR (11), AR (12), AR (16), MA (1), MA (12) are found statistically significant at below 0.05 level. MA (3) is significant at 0.06 level. Insertion of AR (22) and MA (27) resulted in insignificant parameters of these two.

Table 4.4b: Estimates of DIP

	AR(1,3,4,5,8,9,10,11,12,16) MA(1,3,12,13,14,15)	AR(4,10,11,12,16) MA(1,3,12)	AR(4,10,11,12) MA(1,3,12)
m	0.272(3.362)	0.191(1.583)	0.268(3.154)
ϕ_1	-0.089(-1.130)	---------	---------
ϕ_3	-0.098(-1.739)	---------	---------
ϕ_4	-0.251(-3.035)	-0.199(-2.591)	-0.078(-1.557)
ϕ_5	-0.088(-1.521)	---------	---------
ϕ_8	-0.058(-1.035)	---------	---------
ϕ_9	-0.022(-0.422)	---------	---------
ϕ_{10}	-0.159(-3.155)	-0.142(-2.859)	-0.131(-2.595)
ϕ_{11}	0.108(2.025)	0.133(2.660)	0.129(2.527)
ϕ_{12}	0.763(10.937)	0.771(13.497)	0.740(12.905)
ϕ_{16}	0.187(2.295)	0.167(2.093)	---------
θ_1	-0.465(-4.811)	-0.516(-7.703)	-0.552(-8.358)
θ_3	-0.126(-1.515)	-0.167(-2.500)	-0.164(-2.538)
θ_{12}	-0.315(-2.990)	-0.270(-4.400)	-0.240(-4.237)
θ_{13}	-0.082(-0.756)	---------	---------
θ_{14}	0.037(0.347)	---------	---------
θ_{15}	0.005(0.067)	---------	---------
s.e.R	4.165	4.210	4.246
SSR	2637	2837	2975
AIC	2.948	2.927	2.937
SBC	3.263	3.093	3.083
Q(n/4)	40.783(0.033) (lags = 42)	44.169(0.114) (lags = 42)	59.37(0.008) (lags = 43)

At third column, the all parameters, except constant term, are significant at 0.05 and 0.01 levels. When MA (25) was included in this model, it was not found significant. All parameters at column four, except AR (4), are also statistically significant.

First model at second column would be a tentative model. The other two models, hence, are alternative models to be tested. In terms of goodness-of-fit measures, ARIMA (16,1,12) model seems the best to be forecast. Therefore the final model would be the one at column three with the parameters of constant, AR (4), AR (10), AR (11), AR (12), AR (16) and MA (1), MA (3) and MA (12).

5.Exponential Smoothing Model Selection for INT And IP

Exponential smoothing procedure considers the nine possible exponential smoothing techniques in a trend and/or seasonal model: No trend, linear trend or exponential trend; no seasonal, additive seasonal and multiplicative seasonal (RATS, 1992, 14-78,80). RATS chooses the best one among other possibilities on the basis of least sum of squares and least Schwarz criterion. Tables 4a. and 4b. gives the ultimate best choices for INT and IP. These time series then will be forecast section VI by exponential smoothing procedure by using the information obtained from these tables below.

Table 4a: Exponential Smoothing Model Selection for INT

TREND	SEASONAL	Sum Squares	Schwarz
None	None	2989.619	1501.773
None	Additive	2909.432	1501.920
None	Multiplicative	3091.208	1513.253
Linear	None	2995.955	1507.400
Linear	Additive	2918.372	1507.725
Linear	Multiplicative	3099.865	1519.007
Exponential	None	2850.841	1498.116
Exponential	Additive	3.238149e+010	4541.252
Exponential	Multiplicative	2995.083	1512.577
Model with TREND =Exponential , SEASONAL = None			

Table 4b: Exponential Smoothing Model Selection for IP

TREND	SEASONAL	Sum Squares	Schwarz
None	None	6826.859	1647.349
None	Additive	3749.875	1541.134
None	Multiplicative	3605.972	1533.855
Linear	None	6683.461	1648.626
Linear	Additive	3810.244	1549.330
Linear	Multiplicative	3509.135	1534.018
Exponential	None	6512.811	1643.815
Exponential	Additive	3681.086	1542.916
Exponential	Multiplicative	3528.763	1535.055
Model with TREND =None , SEASONAL = Multiplicative			

6. Forecast Values of INT and IP

All I have done so far is just to establish the forecasting models. Now we could reach the forecast values given in Tables VI.a and VI.b, by the help of estimation results of these models obtained in previous sections.

Table 4.a: Forecast Values of INT

	Actual values	Forecast by ARIMA	Forecast by Esmooth
2000:1	37.4	----	----
2000:2	38.9	----	----
2000:3	37.4	----	----
2000:4	38.6	----	----
2000:5	36.0	----	----
2000:6	36.9	----	----
2000:7	35.1	----	----
2000:8	na	28.18	34.31
2000:9	na	29.26	34.13
2000:10	na	31.28	33.94
2000:11	na	30.92	33.76
2000:12	na	30.86	33.58

na: not available

Table 4.b: Forecast Values of IP

	Actual values	Forecast by ARIMA	Forecast by Esmooth
2000:1	85.30	----	----
2000:2	93.80	----	----
2000:3	93.50	----	----
2000:4	96.90	----	----
2000:5	103.70	----	----
2000:6	104.50	----	----
2000:7	na	100.19	97.49
2000:8	na	95.62	96.91
2000:9	na	103.02	106.60
2000:10	na	107.10	111.95
2000:11	na	110.86	110.90
2000:12	na	104.78	107.22

na: not available

Indeed, as we figure out from the tables above, monthly interest rate tends to decrease and monthly industrial production index tends to increase as compared the trends of these variables over indicated sample periods.

7.Conclusion

I employed, here in this study, two widely used forecasting techniques, ARIMA and exponential smoothing procedures to forecast monthly interest rates and industrial production index. First variable, interest rates, is one of the leading indicators for monetary sector and the second variable, production index, is one of the leading indicators for real sector.

Government targets for the year 2000 are to realize a stable reduction in interest rates and a steady increase in real output. After we estimated the models by ARIMA and Exponential smooth methodologies, we obtained the forecast values of interest rates and production index. Provided that we are in a %95 confidence interval, we can say that these forecasting methodologies verify that government's main macro targets will be most likely realized for 2000.

One can, however, carry out also some other forecasting methods such as forecasting from system equations or combined forecasting methods. Or, one can divide the samples into two sub periods in which different policy structures existed and then employ the several forecasting methodologies. These, of course, require another studies that should be done in the future.

ÖZET

Türkiye ekonomisinin 2000 yılı ve sonrası için temel makro hedefleri, faiz oranlarının kabul edilebilir bir seviyeye düşürülmesi ve toplam üretimde sabit bir büyümenin sağlanmasıdır. Bu çalışmanın amacı, hükümetin 2000 yılı için ilgili hedefleri gerçekleştirip gerçekleştiremeyeceğini görebilmektir. Bu amaçla, bu çalışmada, mevduat faiz oranları ve sanayi üretim endeksinin aylık gelecek değerlerini tahmin etmek için Box-Jenkins ve exponential smoothing metodları kullanılmaktadır. Tahmin sonuçları, faiz oranlarının düşme eğiliminde ve sanayi üretim endeksinin yükselme eğiliminde olduklarını göstermektedir. Böylece, kullanılan tahmin teknikleri, hükümetin, büyük olasılıkla, temel hedeflerini 2000 yılı için gerçekleştirebileceğini doğrulamaktadır.

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